ANN and Elements of Differentional Games in the Model of Regulated Wheel Slippage Process in a Braking Mode

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***Abstract* — Processes of braking system operations of the ground wheeled vehicle are complex nonlinear dynamic processes. When a problem of modeling vehicle braking process is setting it is considered rational to set the one in a form of the antagonistic differential game and to represent one of the antagonists – the road surface – in a form of unknown disturbance. It is considered rational to choose an artificial neural network (ANN) as a control element and flexible approximator that has properties of self-learning.**

***Keywords* — braking, control, fuzzy, neural network, differential game, optimization**

I. Introduction

To continue the development of ideas proposed in articles [1] and [2] we consider the possibility of ANN using to solve Hamilton-Jacobi-Bellman equations in the problems of wheel braking modes of ground vehicles. As noted in the article [1], a non-standard and at the same time effective way can be to represent the braking process in a form of the antagonistic differential game. The first player is a wheel, and the second is a road surface. At the same time, the article [2] provides a justification to use ANN in the mathematical model of a braking system with controlled wheel slippage relative to the road surface. Let's consider a combination of both methods as a way to increase the efficiency of the braking system.

II. A PROBLEM STATEMENT

The task involves the development of a neuro-fuzzy controller of the braking system for a ground wheeled vehicle. The system must be resistant to disturbances (robust). The braking control system must be able to optimize for several criteria.

III. AN OVERVIEW OF EXISTING SOLUTIONS

Let's look at the history of ABS development as the most famous of the systems with controlled wheel slippage relative to the road surface. The appearance of the ABS concept in the second quarter of the XX century required the search for effective technical solutions [3]. Up to the 70s of the XX century, ABS systems were implemented as analog devices. ABS systems were not widely used and were mainly used in aviation and single models of ground vehicles [3]. The spread and development of technologies, including microprocessor electronics [4] and fuzzy set theory [5] in control systems has also affected the automotive industry. Fuzzy controllers were used where the use of previously available relay and PID controllers was not possible or unreasonable due to the complexity or impossibility of compiling a mathematical model of the system [6], [7], [8], [9]. In the 80's of the XX century in Japan serial models of a wide variety of equipment were already produced using fuzzy controllers [10], cars were equipped with fuzzy automatic transmission and ABS controllers [10], [11]. Further development of early fuzzy ABS control models [11] led to the appearance of their numerous hybrids. At a certain stage in the development of ABS control systems in addition to the nonlinear control systems as sliding mode control (SMC) [12] and early forms of intelligent control [13] including Mamdani controllers [14], PID-type fuzzy Sugeno or Takagi-Sugeno-Kang controllers were widely used [15]. In 1989 Cybenko [16] and Hornik [17] published papers on the possibility of considering ANN as a universal approximator. In 1994 Kosko demonstrated the possibility of using fuzzy systems as universal approximators [18]. The parallel development and spread of fuzzy systems and ANN made it possible to consider the fuzzy model as a multilayer perceptron [19], [20], [21]. There were trained fuzzy models in the form of neural networks, which quickly became widespread in automatic control systems [20], [21], [22] including ABS of cars [23], passenger and commercial vehicles. The first control systems with ANN for ABS had the properties of nonlinear PID-type controllers. There were also other implementations in the form of ANN, based, for example, on the methods of optimal, adaptive, robust control [24], [25]. On the other hand, the development of neural networks made it possible to use ANNs as calculators [26], [27]. The technologies of computing on GPUs that became available and widespread in the 2010s made it possible to effectively solve systems of differential equations [28], as well as to carry out in-depth training of ANNs [29]. The unique properties of ANNs allowed them to become a powerful tool for solving automatic control problems in nonlinear dynamic systems [19], [20].

Consider the state of development of the theory of automatic control (ACT). Let us to skip the discussion of the first stages of development and use inertial devices [30] and move on to the era of all over the world electrification. So we will talk more about electrical and electronic controllers than about mechanical. For example the most widely used controllers for a long time are PID and PID-type controllers that principles were invented by Minorsky in 20’s of XX century [31]. Theory of automatic control is closely linked with theory of stability. There are some approaches of theory of stability, e.g. Lagrange’s stability [32], Lyapunov's stability [33], Poisson's stability [34], Poincare's stability [35] etc. There are some kinds of technical stability and we can note here about Bogusz's and Szpunar's senses of stability [36]. We know Routh-Hurwitz theorem and Routh-Hurwitz criterion for linear systems [37]. Nonlinear control systems are usually based on Lyapunov's theory of stability. We know Lyapunov's [38] and Chetaev's [39] theorems [40]. There are well known and widely used open-loop and closed-loop systems. The achievements of Soviet Union and Russian scientific school of ACT are presented in main works of Besekersky [41], Mensky and Makarov [42], and others [43]. In ABS modeling automatic control systems (ACS) with feedback (closed-loop) are usually used [44]. We note the methods of hierarchical, intelligent, stochastic, optimal, adaptive and robust control [45], [46]. In recent decades, there has been a trend of increasing use of fuzzy and neural systems in ACS. Different methods were being used in different periods of ABS design, for example [12], adaptive [47], and robust [48] controllers of braking systems and their combinations are known. Developments of the last decade are usually implemented in a form of systems with fuzzy and neurocontrollers [47], [48], [49], [50].

Now let's move on to the issue of optimization. Genetic algorithms [51] are widely used optimization methods relatively to fuzzy systems and ANN, which, however, are not considered in the context of this work. At the same time, a common way to improve control efficiency in dynamic systems is to consider problems in the forms of differential games [52], [53]. Game theory, which was developed in the 40's of the XX century, focused on problems of the economic plan [54] and problems of military confrontation. The main provisions of the theory of differential games are presented in works of Isaacs [52], Bellman [53]. Scientific developments in game theory of the Soviet Union school are presented in works of L. S. Pontryagin [55], Krasovsky and Subbotin [56], [57]. In the future, in this paper, the problems of differential game theory will be considered from the point of view of Bellman's dynamic programming [53]. The theory of antagonistic differential games for two players is studied and worked out well. There are works devoted to the consideration of differential games for several players, for group interaction, with different strategies, etc. There is also a probabilistic approach to the problems of game theory, highlighted in a separate direction – stochastic differential games. In our days the theory of games continues to evolve. Antagonistic differential pursuer – evader games are widely used in robotics tasks related to increasing the energy efficiency of systems [57]. Finding solutions for functionals of nonlinear systems often involves considerable computational complexity. There are various methods for solving such optimization problems, in particular, it is possible to find solutions using ANNs [26], [27], [59]. Existing developments in the field of application of game theory in a form of ANN to wheel braking problems could not be found in the open access. So, the task of using ANN and elements of game theory in problems of controlled wheel slippage modeling process in a braking mode is relevant and in demand for finding a solution.

IV. A RATIONALE FOR CHOOSING A CONTROL METHOD

When considering a model that is close to real conditions we can recommend to use an ANN feedback system as a control element that solves problems in the formulation of antagonistic differential games [26]. The method proposed by the authors [60] allows us to find solutions that are close to optimal values. Since it is extremely difficult to assess the characteristics of the wheel's adhesion to the road surface in practice, it is assumed that a robust control system (based on the H_∞-theory) is used for the braking process [45]. Further complication of the problem may be caused by the influence of unknown perturbations on the system. In such cases, optimal control of the system becomes ineffective. For such problems it is recommended to use control systems. In the process of solving, the authors [26] propose to consider an antagonistic differential game in which the players are on the one hand — the controlling influence, on the other – the disturbance:

$$V\big(x(t)\big) = \int_t^\infty r(x,u,d)dt = \int_t^\infty (h^T(x)h(x) + \left\|u(t)\right\|^2 - \gamma^2\left\|d(t)\right\|^2)dt$$

where $u(t)$ – control input, $d(t)$ - disturbance, $z(t)$ - performance output, that

$$\left\|z\right\|^2 = h^T h + \left\|u\right\|^2$$

and

$$\frac{\int_0^\infty \left\|z(t)\right\|^2 dt}{\int_0^\infty \left\|d(t)\right\|^2 dt} = \frac{\int_0^\infty (h^T h + \left\|u\right\|^2) dt}{\int_0^\infty \left\|d(t)\right\|^2) dt} \le \gamma^2$$

where V^* is defined by

$$V^*\big(x(t)\big) = \min_{u(t)} \max_{d(t)} \int_t^\infty r(x,u,d)dt$$

will be the solution of the Hamilton-Jacobi-Isaacs equation [60]. An algorithm for solving the Hamilton-Jacobi-Isaacs equation using ANN is proposed by the authors [26]. Further improvement of the automatic control system involves the use of a self-learning system control element. An effective way of learning is Q-Learning that is an algorithm based on one of the variants of Bellman's dynamic programming theory (Action Dependent Heuristic Dynamic Programming) [61]. Relatively to ANN in particular to self-learning neuro-fuzzy control systems, the Q-Learning algorithm is successfully used for the optimization of processes described by antagonistic differential games.

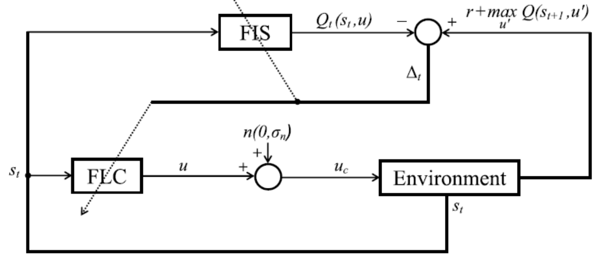

Figure 1 – Q-Learning training of a neural network controller [62]

For example, in [62] we consider in detail the Q-Learning algorithm for training a fuzzy controller to find an effective solution to the pursuit-evasion problem. Thus, it is assumed to use a robust control system (based on the H_∞-theory) implemented in the form of an ANN that is capable of learning.

V. A RATIONALE FOR CHOOSING AN OPTIMIZATION METHOD

A problem of optimizing the braking process can be considered relatively to several parameters, for example, proposed in [1]:

$$I = \alpha \int_0^T |V_x(t)|dt + \beta \int_0^T |M_z(t)|dt$$

or

$$I = \alpha \int_0^T |V_x(t)|dt + \beta \int_0^T |\frac{M_z}{F_{\text{тр}} R}|dt$$

where α, β – some coefficients, V_x - linear velocity of the wheel, M_z - braking torque, $F_{\text{тр}}$ – friction force, R- radius of the disk. The first quality criterion allows us to evaluate the efficiency of the braking process in achieving the minimum stopping distance with minimal energy consumption. The second quality criterion allows us to evaluate the efficiency of energy consumption in the braking process in achieving the highest value of the friction force at the lowest value of the braking torque [1]. Multi-criteria optimization problems can usually be solved either by using the Pontryagin's maximum principle, or by using Bellman's dynamic programming [53], [55]. In the problem described above, we will use methods of the Dynamic Programming theory. As a result of these transformations, we obtain an equation whose solution will be the solution of the optimization problem for a nonlinear feedback system. Here we encounter a problem, since the Hamilton-Jacobi-Bellman equation cannot be solved for most nonlinear systems. However, in the case of linear systems, the Hamilton-Jacobi-Bellman equation is reduced to the Riccati equation, which can be solved effectively [63]. However, most of the current systems that require solving this type of engineering problems have pronounced nonlinear characteristics [64]. As an effective ways of solving the above generalized Hamilton-Jacobi-Bellman equation, authors [60] suggest the use of ANNs. Algorithms for solving the Hamilton-Jacobi-Isaacs equations using ANNs are proposed by authors [29], [65]. Thus, it is assumed that the system can be optimized by using Bellman's dynamic programming methods (based on the Theory of Games) implemented in a form of ANN.

VI. A CONTROL ELEMENT

The proposed model is a control element that includes two ANNs. The first ANN is an implementation of a trained robust controller. The controller ANN has one input and one output. The number of neurons in the hidden layers of the ANN is chosen empirically. The second ANN is an optimizing element and is an implementation of the differential game process. The second ANN includes a block for solving partial differential equations. The ANN of the optimizing element has one input and one output too.

The process of differential game of a robust controller occurs during its activity. In this differential game the control signal and the worst value of the disturbance are opposed. The process of differential game of the optimizing element occurs during training. In this differential game, there is a confrontation of parameters corresponding to the specified optimization criterion. Training of the ANN of a robust controller is based on the results of processing the specified parameters of the ANN of optimization block. In the figure below, $q(t)$ is the disturbance, $z(t)$ – performance output, $x(t)$ – measured output, $u(t)$ is the output of a neurocontroller (or control input), I – optimization criterion.

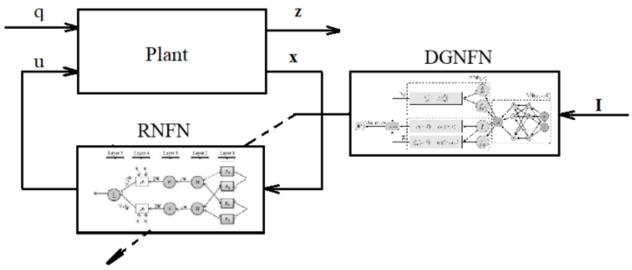

Figure 2 — The architecture of a control unit whith ANN of robust controller (RNFN) and with ANN of optimizing element (DGNFN).

It is assumed that the proposed model of a braking system controller will be able to provide increasing of the system efficiency in a real life exploitation.

VII. CONCLUSIONS

The above justifications indicate a high potential for using ANNs in control and optimization processes of nonlinear dynamic systems [26], [48], [49]. The use of ANNs and elements of the Theory of Games in problems of modeling the process of controlled wheel slippage is an effective and promising direction for the development of methods for solving engineering problems. The direction of further research is seemed in improving of the self-learning neuro-fuzzy model through the use of the latest algorithms for self-learning and optimization of ANNs.

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